J Arid Land (2023) 15(2): 145–163
https://doi.org/10.1007/s40333-022-0083-z

Science Press Springer-Verlag

Integrated water risk early warning framework of the semi-arid transitional zone based on the water environmental carrying capacity (WECC)

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Abstract: Water risk early warning systems based on the water environmental carrying capacity (WECC) are powerful and effective tools to guarantee the sustainability of rivers. Existing work on the early warning of WECC has mainly concerned the comprehensive evaluation of the status quo and lacked a quantitative prejudgement and warning of future overload. In addition, existing quantitative methods for short-term early warning have rarely focused on the integrated change trends of the early warning indicators. Given the periodicity of the socioeconomic system, however, the water environmental system also follows a trend of cyclical fluctuations. Thus, it is meaningful to monitor and use this periodicity for the early warning of the WECC. In this study, we first adopted and improved the prosperity index method to develop an integrated water risk early warning framework. We also constructed a forecast model to qualitatively and quantitatively prejudge and warn about the development trends of the water environmental system. We selected the North Canal Basin (an essential connection among the Beijing-Tianjin-Hebei region) in China as a case study and predicted the WECC in 25 water environmental management units of the basin in 2018–2023. We found that the analysis of the prosperity index was helpful in predicting the WECC, to some extent. The result demonstrated that the early warning system provided reliable prediction (root mean square error of 0.0651 and mean absolute error of 0.1418), and the calculation results of the comprehensive early warning index (CEWI) conformed to the actual situation and related research in the river basin. From 2008 to 2023, the WECC of most water environmental management units in the basin had improved but with some spatial differences: the CEWI was generally poor in areas with many human disturbances, while it was relatively good in the upstream regions with higher forest and grass covers as well as in the downstream areas with larger water volume. Finally, through a sensitivity analysis of the indicators, we proposed specific management measures for the sustainability of the water environmental system in the North Canal Basin. Overall, the integrated water risk early warning framework could provide an appropriate method for the water environmental administration department to predict the WECC of the basin in the future. This framework could also assist in implementing corresponding management measures in advance, especially for the performance evaluation and the arrangement of key short-term tasks in the River Chief System in China.

Keywords: water risk; early warning system; water environmental carrying capacity; prosperity index; water management; North Canal (Beiyun River)

Citation: XIE Yuxi, ZENG Weihua, QIU Jie. 2023. Integrated water risk early warning framework of the semi-arid transitional zone based on the water environmental carrying capacity (WECC). Journal of Arid Land, 15(2): 145–163. https://doi.org/10.1007/s40333-022-0083-z

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Received 2022-07-25; revised 2022-09-26; accepted 2022-09-30

1 Introduction

Rapid socioeconomic development has caused a series of water environmental issues. The increase in water demand has led to the depletion of rivers, and the discharge of water pollutants has resulted in water quality deterioration, especially in semi-arid areas without abundant water resources (Tan et al., 2013). The deterioration of the environment has also restricted and affected regional sustainable development (Usama et al., 2015). Sustainable water management is a significant solution to overcome this risk (Bafarasat, 2021), and the water environmental carrying capacity (WECC) is an effective indicator for evaluating regional sustainability (Kang and Xu, 2012). In China, as water environmental management has changed from the end-treatment after pollution discharge to forward-looking environmental prevention, a series of policy documents have proposed the establishment of a monitoring and early warning mechanism for resources and environmental carrying capacity. Since 2016, Chinese government ministries and commissions have established some monitoring and early warning mechanisms for the WECC and have issued technical guidance documents (e.g., the Monitoring and Early Warning Techniques of Resources and Environment Carrying Capacity and the National Water Resources Carrying Capacity Monitoring and Early Warning Technology Outline). These works, however, are concerned mainly with the comprehensive evaluation of the status quo and lack the quantitative prejudgement and warning of an overloaded state in the future.

Early warning was first applied in the macroeconomic field, which originated from the theoretical hypothesis of the economic cycle first proposed by British economists in 1875 (Knedlik, 2014). The establishment of a global environmental monitoring system called "early warning" was introduced in the environmental field (Yuan, 1987). Nevertheless, most related studies were concentrated on the forecasting of floods (Plate, 2008), early warning of water shortage and water resource carrying status (Yu et al., 2020; Shi and Zhang, 2021), and prediction of water quality and pollutant (Ding et al., 2017; Jin et al., 2019; Imani et al., 2021), whereas very few paid attention to the comprehensive early warning of the water environmental system risk. Although the WECC does not have a uniform definition, it is a broad concept related to the environmental properties of water, and it focuses on the mechanisms of interaction in human (socioeconomic)–water environmental systems (Zhou et al., 2019). The essence of the WECC is to seek the balance between the water environmental system and socioeconomic development. The water environmental system risk is the uncertainty of overload caused by an imbalance between the water environmental system and socioeconomic development. Hence, the WECC can quantitatively measure the risk to the water environmental system by evaluating the overload situation (Dai et al., 2022). Thus, the early warning of water risk based on the WECC is a powerful and practical tool used to guarantee the sustainability of rivers and thus can provide a quantitative basis for watershed management (Lu et al., 2017).

Unlike the long-term early warning (three to five years) that is helpful for long-term planning, the short-term early warning (one to two years) is mainly used for assessing and predicting the water environmental situation in watershed management of the next year. Nevertheless, existing quantitative methods and models for the short-term early warning of the water environmental system are based mainly on the future trend prediction of single and independent early warning indicators and have rarely focused on the integrated change trends of the early warning indicators; these methods and models mainly include the variable fuzzy pattern recognition (VFPR) (Wang and Xu, 2015), autoregressive moving average model (ARMA) (Liu et al., 2019), multiple linear regression model (MLRM) (Wang et al., 2021), gray forecast model (GM) (Lu and Tang, 2019), and artificial neural networks (ANNs) (Maier et al., 2010; Yu et al., 2020; Cao et al., 2021; Chen et al., 2022). In actuality, however, the change in the socioeconomic system is cyclical and is affected by the quantity of flow (e.g., monthly, quarterly, and annual changes). The WECC is a comprehensive concept influenced by socioeconomic development and the endowment of the environment. The indicators of the WECC also should be cyclical because of fluctuations in the socioeconomy. Thus, it would be meaningful to learn from the concept of early economic warning

and provide specific references and guidance for future socioeconomic decision-making and environmental management by analyzing the periodicity of the impact of economic activities on the environment and the WECC.

According to the "measuring business cycles" proposed by Mitchell and Burns (1947), this change in the economic cycle is also called the "boom–bust cycle" that refers to the regular expansion and contraction experienced by economic activities following a general trend of economic development. The prosperity index (boom or climate index) analysis is commonly used in the early warning of economic field to measure the status and trend of economic cycle variation through the fluctuations caused by economic activities (Tu et al., 2016). It is used to evaluate and judge whether or not the economy is booming or in recession, such as the Babson barometer of economic activity and Business Climate Index. On the basis of the research by Mitchell and Burns (1947), Moore (1950) selected 21 representative indicators (leading, consistent, and lagging categories from nearly a thousand economic indicators) to develop the diffusion index (DI) and later collaborated with Shiskin and Moore (1968) to compile the composite index (CI). The CI can effectively overcome the deficiencies of the DI by predicting the turning point of the business cycle and pointing out the intensity of the business cycle fluctuations. The prosperity index analysis method can only qualitatively judge the future trend by analysis of the fluctuations. Thus, this study identified the correlation between the socioeconomic indicators and the WECC to improve the prosperity index analysis method and establish an integrated water risk early warning framework based on the WECC. We also constructed a comprehensive early warning index (CEWI) and its forecast model by simultaneously considering the periodic trends of the pressure and support indicators to qualitatively and quantitatively prejudge and warn about the development trends of water environmental system.

The Beijing-Tianjin-Hebei region is a crucial transition zone between semi-arid and semi-humid areas in China. The North Canal Basin is an essential connection among the Beijing-Tianjin-Hebei region. The North Canal is a typical water-short river, and 70% of its water comes from reclaimed water. The inadequate self-purification capacity of the river is causing severe water pollution and degradation of river ecological functions, thus endangering the health of residents (Meng et al., 2016). In this study, we selected the North Canal Basin as a case study. We verified the feasibility of the integrated water risk early warning framework and proposed corresponding suggestions for the sustainability of the water environmental system. In addition, this framework can provide a scientific method for performance evaluation and the key task arrangement of the River Chief System in China. According to this system, the chief officers of the local governments should also be regional river chiefs and are responsible for the regional water resources management affairs (Liu et al., 2019).

2 Study area

The North Canal (Beiyun River) originates in Beijing and is an important river running through the Beijing-Tianjin-Hebei region (Fig. 1). It is 143 km long (mainstream) and has an area of 6166 km^2, including 25 water environmental management units divided based on the water quality control sections. In 2020, the annual gross domestic product (GDP) of the North Canal Basin was about 3.51×10^{12} CNY, the permanent population was around 24.0×10^6 (Beijing Municipal Bureau Statistics, 2021; Hebei Provincial Bureau of Statistics, 2021; Tianjin Municipal Bureau of Statistics, 2021), and the annual water volume was 10.48×10^6 m^3 (Beijing Water Authority, 2020). The North Canal Basin covers most of the urban area of Beijing, and it is the primary drainage system in Beijing, receiving 80% of reclaimed water from factories and sewage plants every year (Bai et al., 2018). The dense population and developed economy have had a negative impact on the water environmental system. Thus, within the total length of the North Canal in Beijing, in 2020, the area proportion of the water body that is inferior to the water quality category of Grade V (where Grade V represents the water quality standard for the agricultural water and general landscape water areas) in the National Environmental Quality Standards for Surface Water of

China (GB3838-2002; Ministry of Ecology and Environment of the People's Republic of China, 2002) is 6% (Beijing Municipal Ecology and Environment Bureau, 2020).

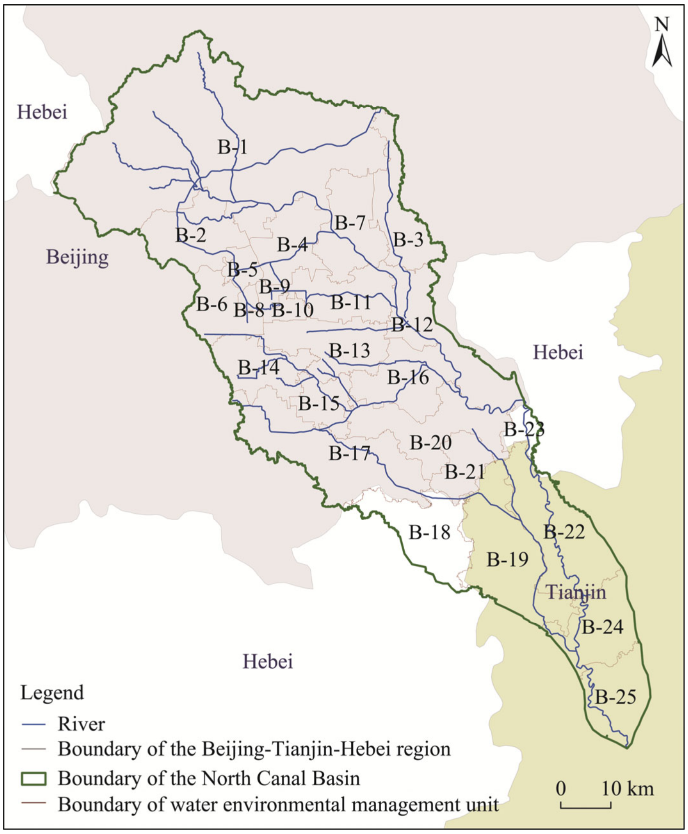

Fig. 1 Overview of the North Canal Basin and the location of the 25 water environmental management units in the North Canal Basin. The base map is from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (https://www.resdc.cn/Default.aspx). Note that water environmental management units are divided by the Chinese Academy of Environmental Planning.

3 Methods

The early warning framework includes six main steps, as shown in Figure 2. The first step involves the definition of the warning situation, which constructs the indicator system after analyzing the impact factors on the water environmental system. The second step identifies warning sources and organizes the indicators for the WECC characterization through the time-difference correlation analysis. The third step includes the judgement of the warning trend to evaluate the tendency for the WECC according to the prosperity index (fluctuation). The fourth step involves the quantitative prediction of the warning situation. This step constructs the CEWI and forecasts its value in the future period. The fifth step divides the warning levels and sets the signal lights, and the sixth step makes suggestions for warning removal and the improvements of the WECC.

3.1 Definition of the warning situation

3.1.1 Establishment of the indicator system

The WECC focuses on the interaction mechanisms in human–water environmental systems. It is an important index to investigate the WECC for human life and production, and can be affected by many factors, such as water resources, water quality, economy, and population (Wang and Xu,

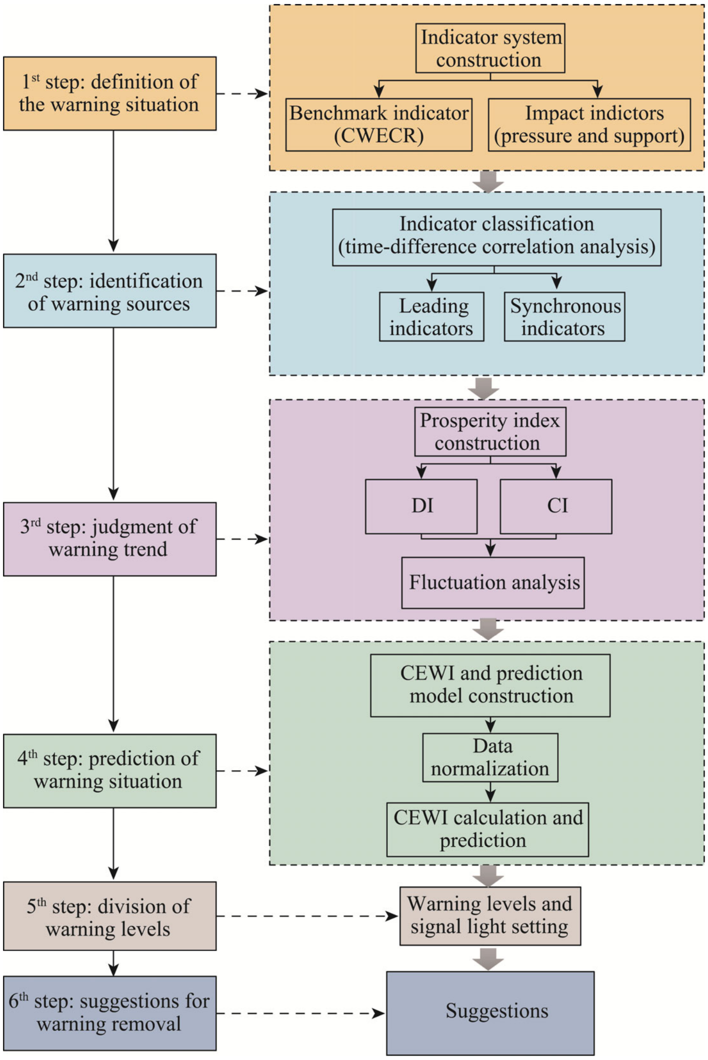

Fig. 2 Integrated water risk early warning framework established in this study. CWECR, comprehensive water environmental carrying rate; DI, diffusion index; CI, composite index; CEWI, comprehensive early warning index.

2015; Zhang et al., 2021). Because this study explored the fluctuations of impact factors and forecasted basin sustainability using the WECC, we selected impact factors from different perspectives to construct the indicator system. We chose these impact indicators according to whether they applied pressure or support from the socioeconomic and water environmental systems. The water environmental system can be classified as water quantity and quality, involving the ecosystem's water conservation (water interception) and water quality purification (pollution interception) capabilities. In addition, the selection of the indicators should ensure the availability of data collection (or calculation). The description of the indicator system is shown in Table 1. Specifically, we selected 17 pressure indicators from socioeconomic development activities on the water environmental system, including population, GDP, water consumption, and wastewater and pollution discharge (e.g., chemical oxygen demand (COD), ammonia nitrogen (NH_4), and total phosphorus (TP)). We also selected 13 indicators that describe the support capacity of the water environmental system, including water resources, sewage treatment capacity, water conservation capacity, water purification capacity (related to the natural vegetation around the water bodies), and environmental protection investment.

Table 1 Description of the indicator system (including the impact indicators (pressure indicators and support indicators) and the benchmark indicator)

System	Pressure indicator	Unit	Support indicator	Unit
Socioeconomy	Total population	10^4	Percentage of environmental protection expenditure in fiscal expenditure	%
	GDP	10^4 CNY		
Water quantity	Industrial water consumption	10^4 t	Surface water resources	10^4 m^3
	Domestic water consumption	10^4 t	Groundwater resources	10^4 m^3
	Agricultural water consumption	10^4 t	Water resources per capita	m^3
	Water consumption per capita	t	Wastewater reuse rate	%
	Water consumption per ten-thousand CNY GDP	t	Water conservation (based on land use)	mm
			Forest and grass coverage (based on land use)	%
Water quality	Point source pollution of COD	t	Water environmental capacity of COD	t
	Point source pollution of NH_4	t	Water environmental capacity of NH_4	t
	Point source pollution of TP	t	Water environmental capacity of TP	t
	Non-point source pollution of COD	t	Number of sewage treatment plants	
	Non-point source pollution of NH_4	t	Sewage treatment rate	%
	Non-point source pollution of TP	t	Water purification capacity (based on land use)	%
	COD discharge per ten-thousand CNY GDP	t		
	NH_4 discharge per ten-thousand CNY GDP	t		
	TP discharge per ten-thousand CNY GDP	t		
	Industrial wastewater discharge	10^4 t		
	Benchmark indicator	Unit		
	CWECR	%		

Note: COD, chemical oxygen demand; NH_4, ammonia nitrogen; TP, total phosphorus; CWECR, comprehensive water environmental carrying rate.

We also needed a benchmark indicator to directly reflect the WECC with suitable periodicity. This benchmark indicator determines the time lag of the pressure and support indicators in the following process (i.e., the time-difference correlation analysis). In this study, a comprehensive water environmental carrying rate (CWECR) that can reflect the WECC was selected as the benchmark indicator, as follows:

$$\text{CWECR}=\sqrt{\frac{[\text{Average}(R_{WR},R_{WE})]^2+[\text{Max}(R_{WR},R_{WE})]^2}{2}}, \tag{1}$$

$$R_{WR}=\frac{U_{WR}}{Q_{WR}}, \tag{2}$$

$$R_{WE}=\text{Average}\left(\frac{P_{\text{COD}}}{W_{\text{COD}}},\frac{P_{\text{NH}_4}}{W_{\text{NH}_4}},\frac{P_{\text{TP}}}{W_{\text{TP}}}\right), \tag{3}$$

where R_{WR} is the water resources carrying rate; R_{WE} is the water environmental carrying rate; U_{WR} (m^3) is the water utilization; Q_{WR} (m^3) is the amount of water resources; P_{COD} (t), P_{NH_4} (t) and P_{TP} (t) are the pollutant discharges of COD, NH_4, and TP, respectively; and W_{COD} (t), W_{NH_4} (t), and W_{TP} (t) are the water environmental capacities of COD, NH_4, and TP, respectively.

3.1.2 Data collection

Most of the data in this study were obtained from the Beijing Area Statistical Yearbook (Beijing

Municipal Bureau Statistics, 2009–2018), Tianjin Statistical Yearbook (Tianjin Municipal Bureau of Statistics, 2009–2018), Hebei Statistical Yearbook (Hebei Provincial Bureau of Statistics, 2009–2018), Langfang Economic Statistical Yearbook (Langfang Municipal Bureau Statistics, 2009–2018), Hebei Rural Statistical Yearbook (Hebei Provincial Bureau of Statistics, 2008–2017), Yearbook of Tianjin Beichen (Local Chronicles Office of Beichen District, 2015–2017), Yearbook of Wuqing (Local Chronicles Office of Wuqing District, 2015–2017), Tianjin Water Resources Bulletin (Tianjin Water Authority, 2008–2017), Beijing Water Resources Bulletin (Beijing Water Authority, 2008–2017), Hebei Water Resources Bulletin (Department of Water Resources of Hebei Province, 2008–2017), and other unpublished department statistics. The environmental pollution discharge data, sewage treatment, and waste reuse relevant data were from the secondary pollution investigation in China (carried out in 2017). The Beijing University of Chemical Technology provided the non-point pollution data. The data on the water environmental capacity were from the previous research results of our research group. The land use data (30 m resolution) were from the interpretation of the Landsat remote sensing images. Considering the data availability, the time span of this study is from 2008 to 2017 and the forecast period is from 2018 to 2023.

3.2 Identification of warning sources

For the early warning accuracy, it is necessary to determine the key factors consistent with the WECC fluctuation cycle. Thus, the time-difference correlation analysis method was used to classify or group indicators into leading and synchronous (coincident) ones (note that this study did not consider lagging indicators). We conducted a time-difference correlation analysis to identify the correlation (time-difference) between the benchmark indicator and the selected indicators. The software used for the analysis was SPSS (Statistical Package for Social Science). The formula is as follows:

$$R_l = \frac{\sum_{t=1}^{N_l}(X_{t+l} - \bar{x})(Y_t - \bar{y})}{\sqrt{\sum_{t=1}^{N_l}(X_{t+l} - \bar{x})\sum_{t=1}^{N_t}(Y_t - \bar{y})}}, \tag{4}$$

where R_l is the time-difference correlation coefficient; l value is the time-difference or time lag (a positive value means lagging, a negative value means leading, and zero means synchronous); t is the time; N is the number of indicators; X is the impact indicator ($X=\{X_1, X_2, \ldots, X_N\}$); Y is the benchmark indicator ($Y=\{Y_1, Y_2, \ldots, Y_N\}$); and $\bar{x}$ and $\bar{y}$ are the average values of X and Y. If R_l is the largest when l=0, the indicator X is the synchronous (coincident) indicator of Y. However, if R_l is the largest when l is negative, it means that the indicator X is the leading indicator of Y.

3.3 Judgement of warning trend

The prosperity index can reflect the comprehensive changes in the impact indicators of the WECC. Therefore, it can be used to indirectly (qualitatively) judge the deterioration or improvement trend of the WECC in the next period. The prosperity index is generally divided into the DI and CI.

The DI can evaluate and measure the fluctuation and change status of the impact indicators. The essence is whether half of the impact indicators are increasing annually (Zhang, 2007). Therefore, when the DI is greater than 50 (prosperous line), more than half of the impact indicators are in a prosperous state. Under the benchmark indicator value, the WECC is a negative indicator (the higher the WECC is, the worse the carrying situation); that is, if more than half of the pressure indicators increase or more than half of the support indicators decrease, the WECC gets worse. When the DI is less than 50, more than half of the impact indicators are depressed; that is, more than half of the pressure indicators decrease, or more than half of the support

indicators increase, and the WECC is improving. Moreover, the leading degree of the leading DI to the synchronous (coincident) DI (time lag is set as *l*) indicates that the change in the WECC will appear after *l* years.

The CI is also called the "prosperity composite index". This index is usually used independently in some economic early warning studies. Its essence is a weighted average of the indicators' changes. The CI can predict the turning point of fluctuations and reflect the change degree (amplitude) of the indicators' influence on the WECC. When the CI is greater than 100 (prosperous line), it indicates that the impact indicators are booming (increasing), and the WECC becomes worse. When the CI is less than 100, it implies that the impact indicators are in a downturn (declining), and the WECC is improving. Furthermore, the leading degree of the leading CI to the synchronous (coincident) CI (time lag is set as *l*) indicates that the change in the WECC will occur after *l* years.

3.3.1 Calculation of the DI

The DI is the percentage of the total number of variables whose time-series changes increase. The formula is given as follows:

$$\mathrm{DI}_t = \left(\frac{\sum_{i=1}^{n} I_P(X_i^t \geq X_i^{t-1}) + \sum_{i=1}^{n} I_S(X_i^{t-1} \geq X_i^t)}{n} \right) \times 100, \tag{5}$$

where DI_t is the diffusion index at time *t*, which is the ratio of the number of the increasing pressure indicators and decreasing support indicators in the next period to the number of all indicators; n is the number of all indicators; I_P is the number of the increased pressure indicators; X_i^t is the value of the i^{th} indicator at time *t*; X_i^{t-1} is the value of the i^{th} indicator at time $t-1$; and I_S is the number of the reduced support indicators.

3.3.2 Calculation of the CI

The calculation of the CI is more complex than that of the DI. The calculation processes are as follows.

First, the CI needs to get the symmetrical change ratio for each indicator by finding the time series of the relative number of cyclic fluctuations based on the original time series of the indicators, as follows:

$$C_{i(t)} = \frac{X_i^t - X_i^{t-1}}{\frac{1}{2}[X_i^t + X_i^{t-1}]} \times 100, \tag{6}$$

where $C_{i(t)}$ is the symmetrical change ratio of each indicator.

Then, the normalization factor of the sequence A_i is quantified using the following equation:

$$A_i = \sum_{i=1}^{t} \frac{|C_{i(t)}|}{h-1}, \tag{7}$$

where h is the number of periods.

The standardized symmetrical change ratio S_i is calculated using Equation 8:

$$S_i = \frac{C_{i(t)}}{A_i}. \tag{8}$$

Next, the average rate of change $R_{(t)}$ can be determined using the following equation:

$$R_{(t)} = \frac{\sum S_i W_i}{\sum W_i}, \tag{9}$$

where W_i represents the weight of the i^{th} indicator and is determined by the time-difference correlation coefficient of each indicator.

Assuming that $I_{(t)}$=100 (where $I_{(t)}$ denotes there is no fluctuation trend), then we would have:

$$I_{(t)} = I_{(t-1)} \times \frac{200 + R_{(t)}}{200 - R_{(t)}}. \tag{10}$$

Finally, the formula of the CI is given by:

$$\mathrm{CI}_{(t)} = 100 \times \frac{I_{(t)}}{\bar{I}_{(o)}}, \tag{11}$$

where $\bar{I}_{(o)}$ is the average value of $I_{(t)}$ in the reference period.

By calculating the CI from the pressure and support indicators separately through these steps, we can obtain the integrated CI, which is the ratio of the CI from the pressure indicators to the CI from the support indicators:

$$\mathrm{CI}_{(t)\mathrm{integrated}} = \frac{\mathrm{CI}_{(t)\mathrm{pressure}}}{\mathrm{CI}_{(t)\mathrm{support}}}, \tag{12}$$

where $\mathrm{CI}_{(t)\mathrm{integrated}}$ is the integrated CI; and $\mathrm{CI}_{(t)\mathrm{pressure}}$ and $\mathrm{CI}_{(t)\mathrm{support}}$ are the CI values from the pressure and support indicators, respectively.

3.4 Prediction of warning situation

By selecting the leading pressure indicators and leading support indicators from the previous step, we constructed the CEWI to reflect the comprehensive carrying capacity in advance. To avoid the correlation between indicators that will bias the early warning index by strengthening the trends of the pressure or support indicators, we adopted the factor analysis method to extract the common factor and calculate the CEWI. In factor analysis, we used the principal component analysis method to extract the common factor and applied the maximum variance method to rotate. The Kaiser-Meyer-Olkin (KMO) test and Bartlett's sphericity test were adopted to measure whether the research is suitable for factor analysis, which required the KMO value is higher than 0.50 and the significant statistical test of the Bartlett's sphericity test is less than 0.05 (Li and Liu, 2016). We calculated the component score using the regression method (i.e., the software used for the factor analysis in SPSS).

The formulas are as follows:

$$T_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}, \tag{13}$$

$$F_i = \sum_{i=1}^{m} Coe_i T_i, \tag{14}$$

$$\mathrm{EWI_P}\ (\text{or } \mathrm{EWI_S}) = \frac{\sum_{i=1}^{m} W_i F_i}{\sum_{i=1}^{m} W_i}, \tag{15}$$

$$\mathrm{CEWI} = \frac{\mathrm{EWI}_P}{\mathrm{EWI}_S}, \tag{16}$$

where T_i is the normalized indicator; X_i is the leading pressure or leading support indicator selected in step 2 (identification of warning sources); $X_{\max}$ and $X_{\min}$ are the maximum and minimum values, respectively; F_i is the factor; m is the total number of factors; Coe_i is the component score coefficient of indicator i; $\mathrm{EWI_P}$ and $\mathrm{EWI_S}$ are the pressure early warning index and support early warning index, respectively; and W_i is the contribution rate of each factor.

By referring to the calculation formula of the CI, we constructed a prediction model to calculate the CEWI in the next period, which was related to the change rate of the leading integrated CI for the next period and the CEWI at the last two periods. The change rate of the leading integrated CI for the next period can be calculated through a time-series analysis. The

formula can be expressed as follows:

$$\mathrm{CEWI}_{t+1}=\mathrm{CEWI}_t\times\frac{[1+\frac{(RCI_{t+1}+1)(\mathrm{CEWI}_t-\mathrm{CEWI}_{t-1})}{(\mathrm{CEWI}_t+\mathrm{CEWI}_{t-1})}]}{[1-\frac{(RCI_{t+1}+1)(\mathrm{CEWI}_t-\mathrm{CEWI}_{t-1})}{(\mathrm{CEWI}_t+\mathrm{CEWI}_{t-1})}]},\tag{17}$$

where CEWI_{t+1} is the comprehensive early warning index for the next period t+1; CEWI_t is the comprehensive early warning index at time t; CEWI_{t-1} is the comprehensive early warning index at time t–1; and RCI_{t+1} is the change rate of the leading integrated CI for the next period t+1.

This study used the root mean square error (RMSE) and mean absolute error (MAE) to evaluate the performance of the prediction model. The RMSE and MAE are two absolute error measures used in a wide variety of disciplines (Karunasingha, 2022). The RMSE reflects the absolute deviation between the predicted and actual values, and the MAE represents the relative deviation. In general, the lower the RMSE and MAE values, the better the performance of the model.

3.5 Division of warning levels and setting of signal lights

The CEWI is the ratio of the pressure early warning index to the support early warning index (Eq. 16). Therefore, we set 1.000 as the status of not overloading and 0.500 as the interval. The early warning signal lights represent the WECC. The warning levels and the corresponding explanation are given in Table 2.

Table 2 Classification of waring levels and the corresponding explanation

Signal light	Waring level	Range of the CEWI	Explanation
Red light	Heavy warning	>1.500	The water environmental system has been seriously overloaded, and emergency early warning measures should be taken to prevent irreversible deterioration of the water environmental system.
Yellow light	Medium warning	1.000–1.500	Socioeconomic development significantly affects the water environmental system, which has exceeded the carrying capacity. It is necessary to restrict socioeconomic growth and take adequate measures to reduce pressure.
Green light	Slight warning	0.500–1.000	The impact of socioeconomic development on the water environmental system is moderate.
Deep green light	No warning	<0.500	The socioeconomic system and the water environmental system develop in harmony.

3.6 Suggestions for warning removal

We conducted a sensitivity analysis of the indicators to identify which indicator had the most significant impact on the CEWI for the next period. We decreased each leading pressure indicator by 10% or increased each leading support indicator by 10% at time t, and recalculated the decrease in the CEWI_{t+1} successively. Finally, combined with related research of the North Canal Basin, we proposed measures to eliminate potential risks for the high-risk units of the water environmental system according to two aspects in advance: alleviating or decreasing pressures and enhancing carrying capacities (increasing supports).

4 Results and discussion

4.1 Identification of warning sources

Because the classification of the indicators can be determined on the basis of the correlation coefficient, some studies did not have a secondary screening of classification indicators according to the correlation coefficient, and all indicators were used for further water safety analysis or the evaluation and prediction of the WECC (Ren et al., 2017; Chen et al., 2022). In this study, we retained only those indicators with correlation coefficients greater than 0.500 to make the early

warning more accurately. The classification results of the indicators (as shown in Fig. 3) revealed 11 leading indicators (seven leading pressure indicators and four leading support indicators) and seven synchronous indicators (three synchronous pressure indicators and four synchronous support indicators). The synchronous indicators reflected the current WECC. The current pressure was derived mainly from the agricultural water consumption, non-point-source pollution discharge of COD, and pollution discharge intensity of NH_4. Related research also proved that the North Canal was relatively polluted by organic substances and NH_4 (Yu et al., 2012). These leading indicators can provide an early warning of the WECC and suggest that the time lag is around one to two years. Thus, the leading pressure and support indicators will reflect the WECC about one to two years in advance. Therefore, to improve the WECC, it is necessary to take measures one to two years in advance, especially to reduce the point-source pollution discharges of NH_4 and TP (correlation coefficient higher than 0.700). In detail, the prevention of the potential phosphorus leaching is most needed in the downstream sections of the basin, and cutting off external pollutants could be helpful in controlling the nitrogen pollution of the basin (Liao et al., 2020; Zhang et al., 2020).

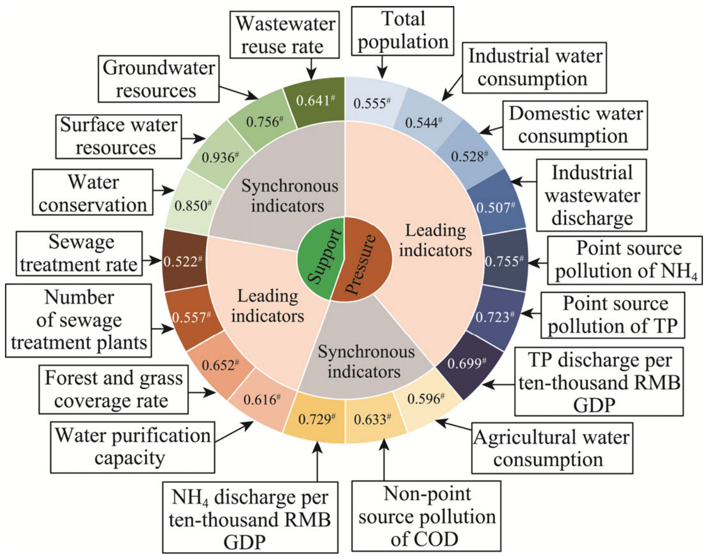

Fig. 3 Classification of the synchronous and leading indicators. # represents the correlation coefficient. COD, chemical oxygen demand; NH_4, ammonia nitrogen; TP, total phosphorus.

4.2 Judgement of warning trend

4.2.1 Analysis of the DI

Because the DI represents a percentage of the increasing pressure indicators or the decreasing support indicators, it can be used to demonstrate whether the WECC is improving or worsening. From the synchronous DI (see Fig. 4a), we can see that the values exceeded 50 in 2010, 2014, and 2017. These values indicated that the WECC in those years was worse than in other years.

By examining the peaks and troughs of the cycle, which can be used to judge the adaptability of the selected indicators (Chen et al., 2011), we found a time lag (from zero to two years) between the synchronous DI and leading DI, which implied the excellent advancement of the leading indicators. According to the time lag, we could infer that the synchronous DI might reach its next peak in 2017, 2018, or 2019. Furthermore, the leading DI trended downward in 2017, suggesting that the WECC is likely to improve or at least would not get much worse in the next period (year).

4.2.2 Analysis of the CI

The CI can be used to simultaneously present the trend and degree of fluctuations, and it also can

comprehensively reflect the WECC (Xie et al., 2019). The synchronous integrated CI (as shown in Fig. 4b) was generally consistent with the changing trend of the benchmark indicator (i.e., CWECR), indicating that the synchronous integrated CI could be used to evaluate the changes in the WECC. Similar to the DI analysis, we observed the peak values of the synchronous integrated CI in 2010 and 2014, suggesting that the WECC in 2010 and 2014 was worse compared with other years.

Analyse of the peaks and troughs of the cycle revealed a time lag (from zero to two years) between the synchronous integrated CI and leading integrated CI, suggesting that the leading indicators are good early warning indices. Hence, the synchronous integrated CI will continue to go up. Despite the uptrend of the leading integrated CI, the value was under 100. This indicated that the WECC would not get much worse in the next period (year).

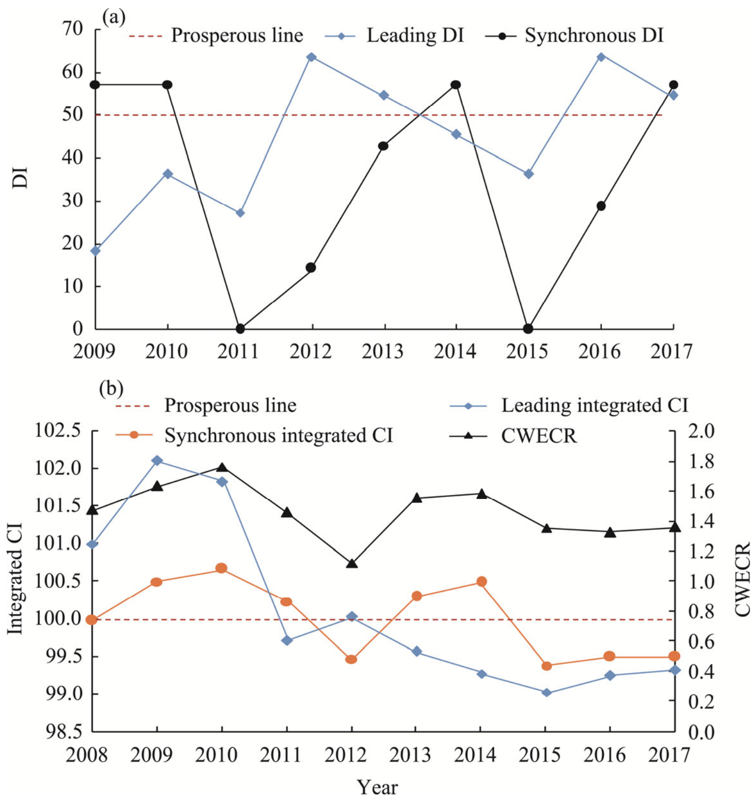

Fig. 4 Changes of the DI (a) from 2009 to 2017 and the integrated CI and CWECR (b) from 2008 to 2017. When the value of the DI or CI exceeds the prosperous line, it indicates that the WECC becomes worsen.

4.3 Prediction of warning situation

4.3.1 Analysis of the CEWI in 2008–2017

To avoid a correlation between indicators, we conducted a factor analysis on the leading pressure and support indicators. The result showed that the KMO values were greater than 0.500 (0.742 and 0.559 for the leading pressure and support indicators, respectively), and the significance of the Bartlett's sphericity test was less than 0.001 (0.000 for both the leading pressure and support indicators), indicating that the selected indicators passed the correlation test and were suitable for the factor analysis (Li and Liu, 2016). The accumulated contribution rate of the first three factors reached 82.293% for the pressure indicators and 89.657% for the support indicators, thus, we extracted the pressure indicators and support indicators with the three common factors

We calculated the CEWI of 25 water environmental management units in the North Canal Basin (Fig. 5a1–a5). After 2013, the WECC of the lower reaches was improved, and in 2017, the overall WECC of the river basin was improved, especially in the middle and upper reaches (which

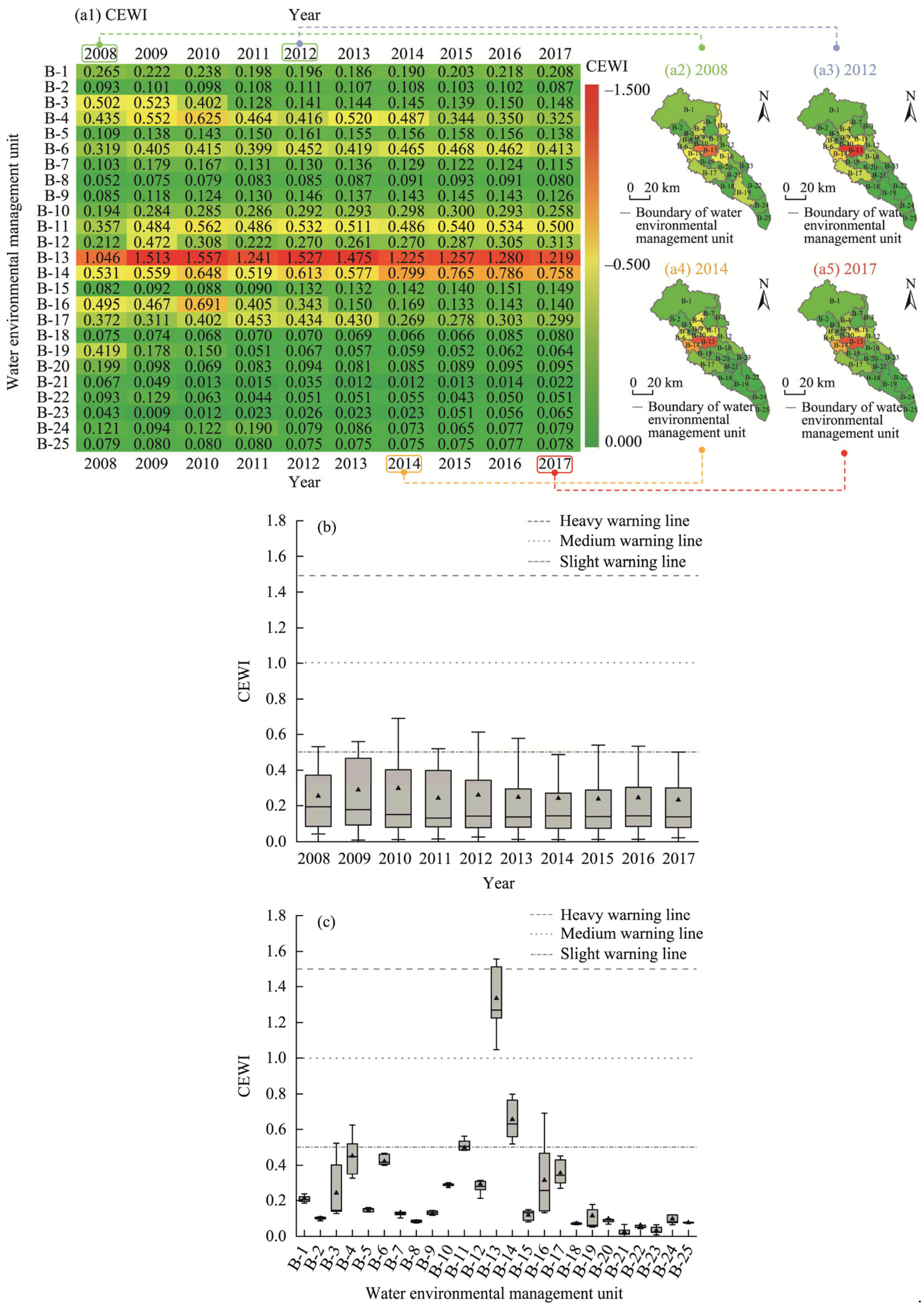

Fig. 5 Temporal variation of the comprehensive early warning index (CEWI) values for the 25 water environmental management units in 2008–2017 (a1), spatial distribution of the CEWI values for the 25 water environmental management units in typical years (a2–a5), and box plots of the CEWI values for the years 2008–2017 (b) and for the 25 water environmental management units (c). The solid line in the middle of the box is the median, representing the general level of the sample data. The symbol triangle within the box is the average, which represents the average level of the sample data. The top and bottom of the box are the upper quartile and the lower quartile of the sample data, respectively. The width of the box reflects the fluctuation degree of the sample data. The upper and bottom whiskers represent the maximum and minimum values (excluding outliers), respectively.

are part of Beijing). The box plots shown in Figure 5b indicate that the CEWI has generally been declining year by year since 2009. Although a slight upward fluctuation occurred after 2014, most of the CEWI values remained below 1.000. Figure 5b shows that the box-shape changes stabilized after 2013, implying that the differences in the WECC status between regions gradually reduced and the overall WECC status was improved. These results are consistent with the actual situation. Since 2013, the government of Beijing has issued two "Three-Year Action Plans" for water environmental treatment and established the River Chief System, covering more than 1200 river reaches. Additionally, 18 reclaimed water plants have been newly built, and three sewage treatment plants were upgraded (Song et al., 2022; Sun et al., 2022). As a result, the effect of water environmental treatment in the North Canal Basin is obvious. The box plots of different water environmental management units in Figure 5c show that the WECC in the urban central areas has been poor and unstable. The CEWI value of unit B-13 exceeded 1.000, the data distribution span was large, and unit B-14 was at risk of being overloaded with a higher CEWI (close to 0.800). Additionally, the vast variations in the CEWI values of units B-3 and B-16 indicated a significant improvement in the WECC of these units, and the water quality of the corresponding sections was also improved significantly in those years (Ji and Lin, 2021; Sun et al., 2022).

4.3.2 Prediction of the CEWI in 2018–2023

Before predicting the CEWI for the 25 water environmental management units for the next period (year), it is important to perform model validation using historical data. Because the CEWI values were relatively stable after 2014 (Fig. 5), we simulated the CEWI values for the 25 water environmental management units in 2014–2017 (100 samples in total) and verified them with the actual values. The comparison results demonstrated good fitting between the simulated values and the actual values (RMSE=0.0651 and MAE=0.1418), indicating that the prediction model established here was reliable (Taylor, 2015).

As shown in Figure 6, other than some water environmental management units (i.e., B-12, B-19, B-20, B-21, B-22, B-23, B-24, and B-25), the CEWI values of the remaining 17 water environmental management units were improved in 2017, which was consistent with the improvement of the water environmental system in recent years. The proportion of the water body that is inferior to the water quality category of Grade V in the National Environmental Quality Standards for Surface Water of China (GB3838-2002; Ministry of Ecology and Environment of the People's Republic of China, 2002) decreased from 60% in 2017 to 6% in 2020 (Beijing Municipal Ecology and Environment Bureau, 2017–2019, 2020). At the same time, the results showed that the fluctuation analysis of the prosperity index (Section 4.2) was helpful in predicting the WECC to some extent.

The spatial distribution of the CEWI values indicated that the WECC of the upstream and downstream regions of the basin would be better in 2023. According to the actual conditions of the basin, this is mainly due to the result of high vegetation cover and less human interference in the upstream region. Moreover, the large flow in the downstream region could have an enhancing effect on the WECC. The sustainability level would be higher in the middle reaches of the North Canal Basin (location of the city centre). Although the overload situation of the water environmental system would be improved, the overloaded risk still exists in unit B-13 (CEWI value of 0.880) because of the high population density, large domestic water, and significant pollution discharge in the central area of Beijing. Additionally, the CEWI of unit B-21 would significantly increase in 2023, and the related water environmental management needs to be strengthened.

4.4 Suggestions for warning removal

The result of the sensitive analysis (as shown in Fig. 7) demonstrated that the total population, domestic water consumption reduction, and water purification capacity enhancement were the three most effective measures for improving the WECC in the basin, and the decreasing in the point source pollution of NH_4 was the key measure for the central city area (units B-13 and B-14).

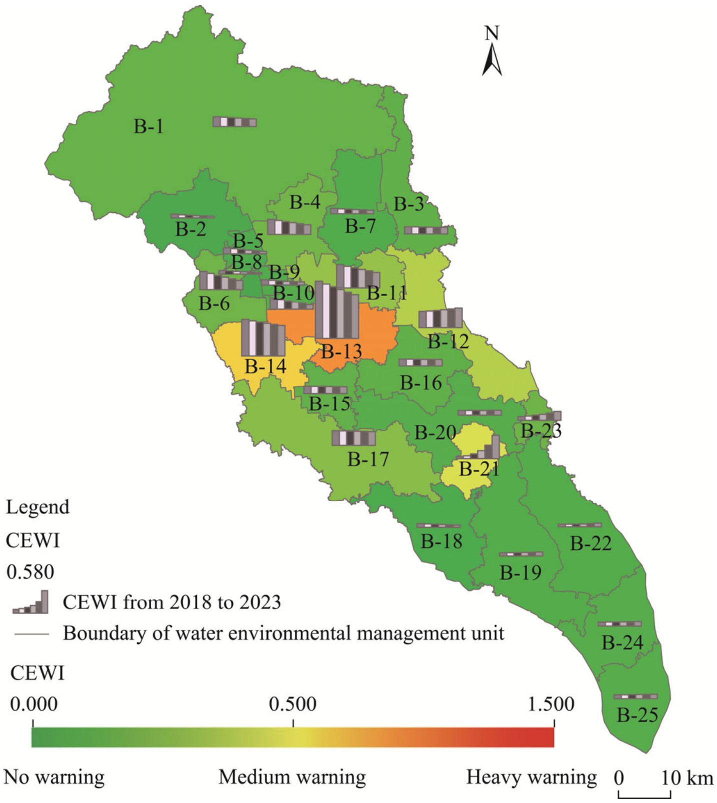

Fig. 6 Prediction of the CEWI for the 25 water environmental management units in 2023 as well as the changes of the CEWI from 2018 to 2023. Note that the histogram represents the CEWI for the 25 water environmental management units from 2018 to 2023.

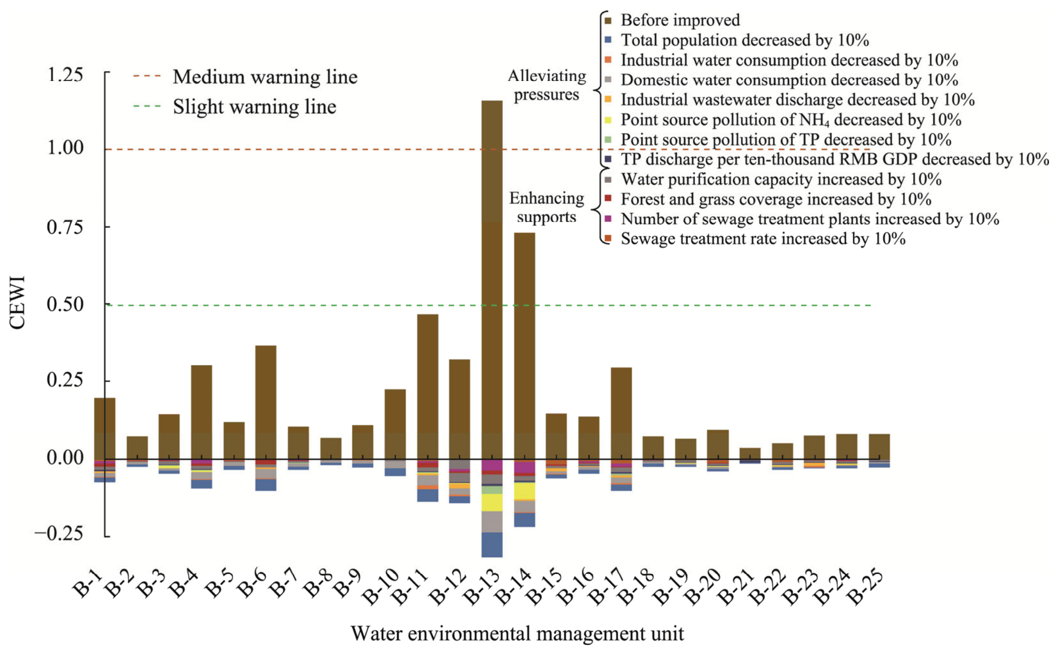

Fig. 7 Comparison of the CEWI for the 25 water environmental management units in 2018 (positive values) and its accumulated decline (negative values) after the changes of each indicator in 2018. Note that the change of indicators was based on the assumed measures (alleviating pressures or enhancing supports) taken.

Significantly, if all assumed measures were taken, the CEWI of unit B-13 would drop below 1.000. In addition, room for improvement existed in units B-6, B-11, B-12, B-14 and B-17 (the accumulated decline of the CEWI was higher than 0.100). Thus, based on the previous analysis, we suggest that the North Canal Basin (especially in Beijing) should control the population size in the future to the degree possible. According to the regional measures of water-saving management, the governments of all districts should make a water use plan, implement strict water quota management, and pursue the laddered water price policy for water consumption units, especially for enterprises with high water consumption. Furthermore, the governments should strengthen water-saving education and publicity and encourage the renovation and installation of water-saving equipment by providing appropriate compensation to water users. Moreover, to enhance the water purification capacity of the ecosystem, the governments should optimize land use patterns. Research on the North Canal Basin has shown that the improvement of eco-environmental quality is related to the increase of vegetation cover (Su et al., 2022), especially the improvement of water quality by increasing in forestland (Liu et al., 2018). The governments should increase the area of ecological conservation regions in urban planning, restrict the further expansion of construction land, and reduce the aggregation of built-up lands and impervious ground in the city (Liu et al., 2021). According to relative research, the wastewater treatment plants are still the main source of pollution in the North Canal Basin (Zhang et al., 2020); thus, the governments should set stricter standards for the effluent indicators to further optimize the water quality in the central city area.

5 Conclusions

From the perspective of economic fluctuation, in this study, we first utilized the prosperity index in economics to construct a water risk early warning system based on the WECC and applied the system to the North Canal Basin as a case study. The results demonstrated that the analysis of the prosperity index was helpful in predicting the WECC status to some extent, the established early warning system was reliable (RMSE=0.0651 and MAE=0.1418), and the calculation results of the CEWI conformed to the actual situation and related research in the river basin. Thus, this index (CEWI) could provide an appropriate method for the water environmental administration department to predict the WECC status of the basin in the future. Thus, it could assist in implementing corresponding management measures in advance, in particular, for performance evaluation and for the arrangement of key short-term tasks in the River Chief System in China.

The results of the case study suggested that the WECC of most water environmental management units in the North Canal Basin is improved. Still, the middle reaches of the basin face the risk of overloading of the water environmental system. Thus, specific management measures need to be implemented in the region, including population control, water quota management, publicity and education on water conservation, renovation and installation of water-saving equipment, land use structure optimization, and setting stricter standards for the effluent indicators.

Acknowledgements

This research was supported by the National Key R&D Program of China (2021YFB3901104). The authors would like to thank the Beijing University of Chemical Technology, China for providing the non-point pollution data.

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